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# USE OF NEURAL NETWORKS FOR FISH IDENTIFICATION FROM SONAR ECHOES - PRELIMINARY RESULTS

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Ontario Hydro is currently investigating the possibility of using sonar to collect quantitative fisheries data as a safer, cost-effective and environmentally attractive alternative to current practices. The present study is a part of that investigation and explores the potential of a neural networks for detecting and classifying the fish from the sonar echoes. Preliminary results are encouraging and a simple neural network was able to identify up to 91 percent of the test samples. When the identification problem is divided into three subproblems, over 93 percent of the samples are identified correctly. If borderline responses are discarded, the success rate increases to over 96 percent.

## 1. INTRODUCTION

Environmental regulations require Ontario Hydro to monitor fish populations and their distributions in the neighbourhoods of generating stations. The Research Division is investigating the potential of sonar to replace, to some extent, the current netting practices, because it is safer, non-consumptive and less labor intensive. One key element of the proposed approach is the identification of the fish from their sonar echoes.

This report is based on the work done during the course of the project "Pattern Recognition using Neural Networks" under the Director's Fund. It summarizes some preliminary results based on laboratory data to explore the potential of neural networks for distinguishing fish from debris and for speciating fish from the sonar echoes. A portion of these results were presented by Ramani, et al (1990).

| job | file | date | report no. |
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| 74-664-090 | 810.0 | October 4, 1991 | 91-226-K |

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## 2. THE NEURAL NETWORK APPROACH

The neural network approach is a biologically motivated statistical method for mapping between vector spaces. It has been proven that any arbitrary continuous mapping between two vector spaces can be realized using a neural network. In recent years, the approach has been used successfully in many pattern recognition applications, where a neural network maps an input pattern vector into an output decision vector. A distinctive feature of a neural network is that there is no algorithmic analysis of the problem, but the network is 'trained' by showing it samples of the desired mapping. Neural networks are particularly useful in cases where the data is noisy, as long as a statistically valid set of example data is available for training.

A neural network consists of an array of interconnected elementary processors (or neurons). The most popular model is called a multi-layer perceptron, where the network is arranged in layers, consisting of an input layer, one or more hidden layers and an output layer. Each neuron in a layer is connected to every neuron in the neighboring layer with distinct interconnection weights. A network performs an input-output mapping as follows. A signal representing the input vector is presented to the input layer. The activation level of each neuron in the other layers is a simple function of the weighted sum of the activation levels of the neurons in the prior layer. That is, the activation level $a_j$ of neuron j is given by

$$a_j = f\left( \Sigma\, w_{ji}\, a_i \right) \qquad (1)$$

where $f(x) = 1/(1+e^{-x})$, $w_{ji}$ is the weight of the interconnection between neuron i and neuron j, and the sum is over all neurons in the prior layer. The activation levels of the neurons in the output layer represent the output vector. The hidden layer usually represents the key to the proper mapping by capturing functional representations that are not obvious in the input vector. These networks are also often called feedforward networks, because information propagates forward (layer by layer) through the network without any feedback.

The network starts with random weights and the weights are adapted, ie, the network is 'trained' to realize the appropriate mapping by showing it examples of the proper mapping. The commonly used adaptation algorithm is called the back-propagation algorithm (Rumelhart, Hinton, and Williams, 1986) and is outlined below. It uses the gradient descent method to minimize the sum of the squared error at the output layer between the actual output and the expected (or target) output over all the training cases.

Rumelhart et al show that the weight change algorithm is given by the following equations:

$$\Delta w_{ji} = \alpha\, \delta_j\, a_i \qquad (2)$$

$$\delta_j = (t_j - a_j)\; a_j\; (1 - a_j), \qquad (3a)$$

$$\delta_j = a_j\; (1 - a_j)\; \Sigma\, \delta_k\, w_{kj} \qquad (3b)$$

where $\alpha$ is the learning rate, $t_j$ is the target and $\delta_j$ is the error signal. $\delta_j$ is given by equation (3a) if neuron j is in the output layer, and by equation (3b) if neuron j is not in the output layer. Note that the summation in equation (3b) is over all the neurons in the subsequent layer. One can see that the gradient of the error propagates backward from the output layer giving rise to the name of the algorithm.

To improve convergence, Rumelhart et al suggest the use of momentum term as well, so that the weight change at iteration n+1 is given by

$$dw_{ji}(n+1) = \alpha\, \delta_j\, a_i + \beta\, dw_{ji}(n) \qquad (4)$$

where $\beta$ is the momentum factor. The above algorithm, with some minor modifications, is used in this study.

## 3. DATA

A dual beam (6 degrees and 15 degrees) 420 kHz transducer (Biosonics) with time varied gain was used for the acoustic sampling. The reflected signals were received through a Biosonics 101 sounder and a wideband sonar detection module (Patrick et al, 1991), and were recorded using an FM recorder (Racal Store 7). The recorded data were digitized at a 60 kHz sampling rate for use by the neurocomputer (SAIC). A block diagram of the data collection and analysis system is shown in Figure 1.

The sampling was conducted in the laboratory where the transducers were placed horizontally in a large semi-anechoic tank measuring approximately 15.5 m in length and width and 1.5 m in depth. The dual beam transducer was placed at one end of the tank, and the targets were placed approximately 6 m from the transducer.

Data were collected on single targets which included a ping pong ball, a leaf, air bubbles (defined as debris) and four species of fish (walleye *Stizostedion vitreum 70 cm* T.L., rainbow trout *Salmo gairdneri* 27 cm, brown bullhead *Ictalurus nebulosus* 23 cm, sturgeon *Acipenser fulvescens* 80 cm). Although it is somewhat unrealistic that these species and debris would occur in nature at the same time, it was felt that this would represent a good test case. Data collected on fish involved tranquilized (MS 222) individuals suspended using a monofilament. The leaf and the ping pong ball were also suspended in the water column using a monofilament. The monofilament line was not detected using the 420 kHz transducer. A continuous stream of small air bubbles was created using a wand (Bloweve Inc). The four fish samples were positioned laterally (broadside) with respect to the transducer. Two additional sets of signals for the sturgeon, with the fish positioned frontally and at 45 degrees to the transducer, were also collected, making a total of nine targets.

Single target data were obtained using a transmitted pulse width of 0.5 ms. Only the 6 degree data were used and forty eight signals from each of the nine different targets were digitized at 60 kHz. The pulses were transmitted every 0.5 seconds and thus the digitized data consisted of short pulses of signal echoes interspersed by relatively long periods of noise. The signal echoes (192 points each) were retrieved from the digitized data using the transmitted pulse as a guide. Figures 2 and 3 show some sample echoes. It

can be seen from Figure 2 that echoes from the different species can in fact look similar, whereas Figure 3 illustrates the variations in the echoes for a single fish.

## 4. DATA ANALYSIS

### 4.1 The Neural Network Architecture

As mentioned earlier, feedforward networks with three layers of neurons were used and the back-propagation algorithm was used to train the network. The first layer consisted of 192 units and the size of the output layer depended on the subproblem being studied, as described below. The number of units in the middle layer was varied from 10 to 30 units in an attempt to study the impact of the hidden layer size on the results. The weights of the network were initialized to random values between -0.3 and 0.3 and the learning rate and momentum factors ($\alpha$ and $\beta$ in Equation (4)) were set at 0.01 and 0.6 respectively. All the simulations were done on a SAIC Sigma II Neurocomputer workstation.

The training set consisted of 38 of the 48 signals for each of the targets and the remaining 10 were used to test the trained network. Training continued until all the training samples were learned, or until learning saturated. The analysis consisted of three experiments described below.

### 4.2 Experiment 1

The first experiment consisted of a network with nine output neurons corresponding to the nine targets described above. Case A of Table 1 shows the performance of the network on the test set of 90 patterns. As the size of the hidden layer increases, the performance improves, but when the hidden layer size is increased to 30, the performance drops, perhaps a case of overtraining. The best performing net correctly identifies an impressive 91.1% percent of the test patterns. In comparison, the average human ( 10 non-experts) performance on the same set was about 75 percent.

### 4.3 Experiment 2

It was decided that the network would next be tested by dividing the classification problem into three subproblems. In the first stage, the net is asked to differentiate fish from debris; in the second stage, to speciate the fish once the first stage has identified the echo to be that from a fish; and finally in the third stage, to identify the fish angle after the second stage has identified the fish to be a sturgeon. The three stages have 2,4, and 3 neurons respectively in the output layer.

The performance of three-layered networks on these subproblems are shown in Table 1 as case B, case C and case D respectively. The best performances in the three stages are 94.4%, 97.5% and 100% respectively. A combination of the three stages scores 93.3% on the original test set. It is interesting to note in all the cases, the performance increases as the hidden layer is increased to a certain size and then begins to drop.

### 4.4 Experiment 3

The third experiment consisted of accepting only unambiguous responses from the network. In the above cases, the network is forced to come up with a guess for each input signal. Typically, there are $m$ neurons in the output layer to identify $m$ classes. The ideal outputs correspond to corners on an $m$-dimensional hypercube and diagonal hyperplanes are used to divide the space into $m$ regions corresponding to the $m$ classes. Figure 4(a) illustrates the case for $m=2$. It is more logical to allow the network to respond "not sure" when the distance $r$ (suitably defined) from the actual output to the ideal outputs are all greater than a preset value. Figures 4(b) and 4(c) illustrate the idea when the maximum distance allowed, $r$, is based on the Euclidean norm and the max norm respectively. Clearly, as $r$ decreases, the confidence in the response increases at the expense of an increased number of "not sure" responses. Note that, to ensure that two regions of interest do not intersect, $r$ should be less than $r_o$, where $r_o$ is half the distance between two ideal outputs.

Table 2 shows the performances of the nets in the above two experiments with $r = 0.9r_o$ (max norm). In the table, the success rates are based on the unambiguous responses alone. As expected, the accuracy of the net increases (comparing the corresponding cases in Tables 1 and 2) and the best performing net scores over 96 percent in the test set. It was found that (not shown in the table) the accuracy could be increased to 100 percent, if one is willing to accept a 35 percent "not sure" rate. This may indeed be the case in fisheries, since all the fish in a school tend to be of the same species and thus not all the echoes need be identified.

## 5. CONCLUSION

This report has summarized some preliminary work on the use of a neural network, based on the back propagation algorithm, for the detection and classification of fish from sonar echoes. The results on the laboratory data are quite encouraging. The success using only the time domain data is somewhat surprising and is a tribute to the wide band detection module used. Although the results are preliminary, they do demonstrate that the neural network approach offers a viable method for the fish identification problem. Further studies including studies involving fish at other different angles to the transducer, multiple target analysis, as well as evaluations of other network architectures, are in progress.

**ACKNOWLEDGMENT**

This work was supported by the Research Division Director's Fund.

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**TABLE 1 - RESULTS FROM EXPERIMENTS 1 & 2**

SUCCESS RATES (Percent correctly identified on test set)

| Case being studied | Middle Layer Size | | | | |
|---|---|---|---|---|---|
| | 10 | 15 | 20 | 25 | 30 |
| A: All 9 Targets | 77 | 81 | 86 | 91 | 86 |
| B: Fish/Debris | 93 | 93 | 94 | 94 | 94 |
| C: Fish Type | 93 | 98 | 98 | 95 | 95 |
| D: Fish Angle | 94 | 97 | 100 | 97 | 97 |
| E: Best of B+C+D | 93 | | | | |

**TABLE 2 - RESULTS FROM EXPERIMENT 3**

SUCCESS RATES (Percent correctly identified on test set)

| Case being studied | Middle Layer Size | | | | |
|---|---|---|---|---|---|
| | 10 | 15 | 20 | 25 | 30 |
| A: All 9 Targets | 80 (10)[1] | 85 (12) | 87 ( 9) | 96 (17) | 90 (16) |
| B: Fish/Debris | 93 ( 1) | 93 ( 1) | 95 ( 3) | 95 ( 3) | 94 ( 1) |
| C: Fish Type | 97 (13) | 100 (10) | 100 (13) | 100 (13) | 100 (15) |
| D: Fish Angle | 100 (13) | 100 (13) | 100 ( 7) | 100 (10) | 100 ( 3) |
| E: Best of B+C+D | 96 ( 6) | | | | |

[1] Numbers in brackets refer to percent of "not-sure" responses

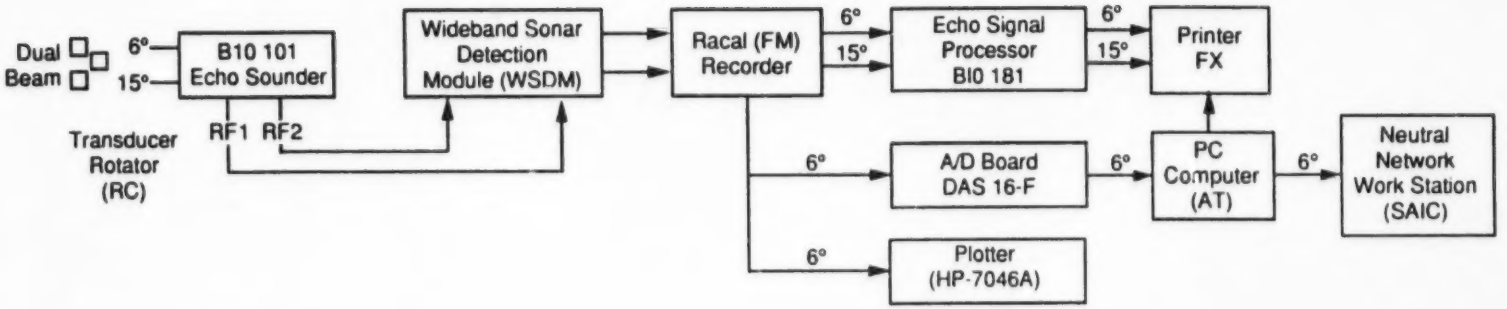
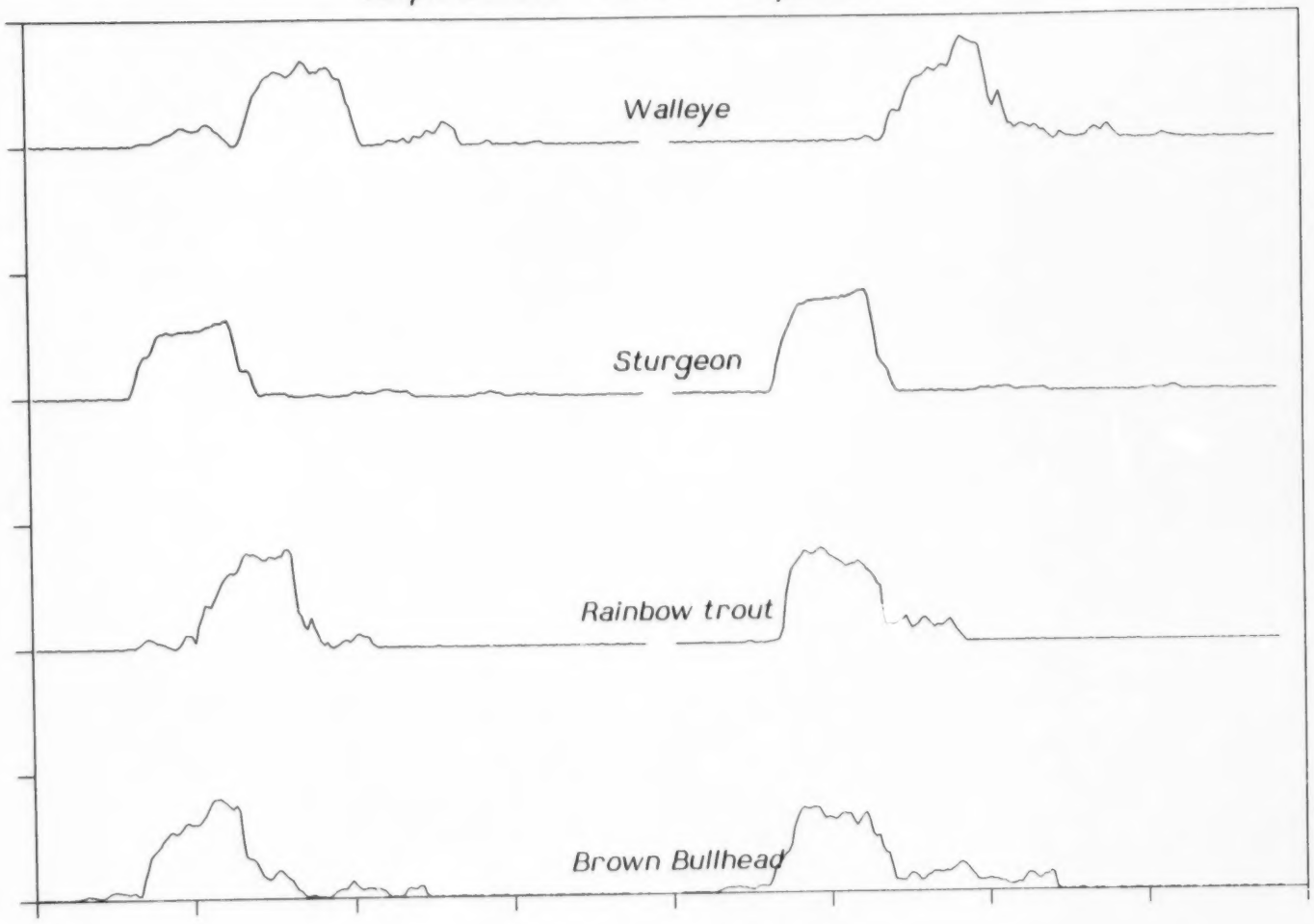



**FIGURE 1**

**DATA COLLECTION AND ANALYSIS SYSTEM FOR SONAR SIGNALS**

# FIGURE 2

*Sample Echoes - 4 Different Species*



# FIGURE 3

*Sample Echoes – Walleye*

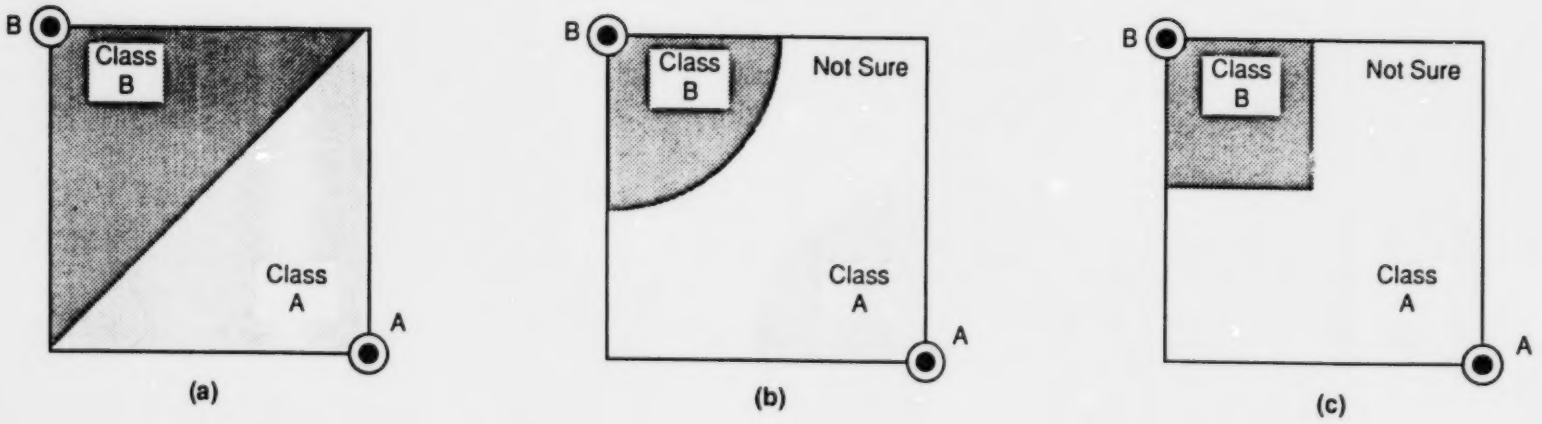



**FIGURE 4**

**ALLOWING "NOT SURE" RESPONSES**